

# Adaptive Channel Equalization for Nonlinear Channels using Signed Regressor FLANN

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**Abstract**—Wireless communication systems are affected by inter-symbol interference (ISI), co-channel interference in the presence of additive white Gaussian noise. ISI is primarily due to the distortion caused by frequency and time selectivity of the fading channel and it causes performance degradation. Equalization techniques are used to mitigate the effect of ISI and noise for better demodulation. This paper presents a novel technique for channel equalization. Here a Signed Regressor adaptive algorithm based on FLANN (Functional Link Artificial Neural Network) has been developed for nonlinear channel equalization along with the analysis of MSE and BER. The results are compared with the conventional adaptive LMS algorithm based FLANN model. The Signed Regressor FLANN shows better performance as compared to LMS based FLANN. The equalizer presented shows considerable performance compared to the other adaptive structure for both the linear and non-linear models in terms of convergence rate, MSE and BER over a wide range.

**Index Terms**—Wireless Communication System, ISI, Channel Equalization, Signed Regressor LMS, FLANN, Signed Regressor FLANN.

## I. INTRODUCTION

High quality and high-speed is the greatest demand in wireless communication. One of the major hindrances in the way of errorless digital communication is inter symbol interference (ISI). ISI may be due to one or more of the factors like: frequency selective characteristics of the channel, time varying multipath propagation in mobile communication. Adaptive Equalizers are employed at the receiver end to compensate the received signals which are corrupted by the inevitable noise, interference and signal power attenuation introduced by communication channels during transmission [1]. Traditionally linear transversal filters are commonly used in the design of channel equalizers. The linear equalizers, however, fail to work well when transmitted signals have encountered severe nonlinear distortion [2].

The use of large constellations provides bandwidth efficient modulation. Quadrature Phase Shift Keying (QPSK) type modulation techniques have constellations, in which signal points are uniformly spread. Information is carried by both signal amplitude and phase; hence they are not constant envelopes. Thus, efficient nonlinear power amplifiers cannot be utilized in the transmitter, without equalization in the receiver [3]. Since Wiener's classical work on adaptive filters, the mean-square-error (MSE) criterion has been the workhorse

of function approximation and optimal filtering [1]. A variety of approaches employing the MSE criterion have been taken towards solving this nonlinear channel equalization problem. The equalizers trained by conventional LMS algorithm perform effectively in case of linear channels. But in practical application, often we encountered with nonlinear channels along with random fluctuating impulse noise. The LMS adaptive tool do not perform satisfactorily for nonlinear channels because of local optima problem. FLANN (Functional Link Artificial Neural Network) is one of the solutions to the problem. FLANNs are mostly trained by back propagation (BP) algorithm [4]. But the convergence speed using BP algorithm is very slow for a large number of input samples. So Sign Regressor LMS is used as the learning tool for FLANN model to equalize the received signal [5].

In this paper the use of Sign Regressor LMS algorithm and Sign Regressor FLANN algorithm for nonlinear channel equalizers have been investigated. Both the algorithms are applied for the design of the channel equalizers in the real as well as complex environment. However both schemes are compared in terms of performance for ensemble square error and bit error rate.

The paper is organized as follows: Section II outlines the Digital Transmission models where QPSK is introduced. Section III describes the conventional LMS and Sign Regressor LMS algorithm and section IV outlines the FLANN as well as Sign Regressor FLANN. Section V discusses the extensive simulation results in nonlinear channel equalization in terms of their effectiveness and section VI concludes the work.

## II. NONLINEAR CHANNEL EQUALIZATION MODEL

An adaptive equalizer is an equalization filter that automatically adapts to time-varying properties of the communication channel. Adaptive channel equalizers has played an important role in digital communication systems. In an adaptive equalizer the current and past values of the received signal are linearly weighted by equalizer coefficients and summed to produce the output [6-8]. It is frequently used with coherent modulations such as phase shift keying, mitigating the effects of multipath propagation and Doppler spreading [9].

Figure (1) represents the block diagram of a digital communication system with adaptive Equalizer. Here QPSK (Quadrature Phase Shift Keying) signal is used as the refer

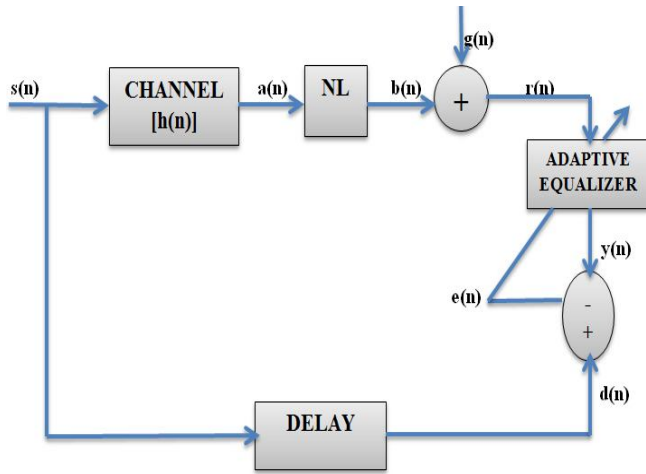


Fig.1. Block diagram of digital communication system with equalizer

ence input signal. The signal  $s(n)$  denotes a sequence of  $T_b$ -spaced symbols of QPSK constellation. QPSK involves the splitting of a data stream  $m_k(t) = m_0, m_1, m_2, \dots$ , into an in-phase stream  $m_i(t) = m_0, m_2, m_4, \dots$  and a quadrature stream  $m_q(t) = m_1, m_3, m_5, \dots$ . Both the streams have half the bit rate of the data stream  $m_k(t)$ , and modulate the cosine and sine functions of a carrier wave simultaneously. As a result, phase changes across intervals of  $2T_b$ , where  $T_b$  is the time interval of a single bit.

The output of the linear dispersive channel at  $n^{\text{th}}$  instant is expressed as

$$a(n) = s(n) * h(n) = \sum_{k=0}^{N-1} h(k) s(n-k) \quad (1)$$

where  $h(n)$  is the impulse response of channel and  $N$  is the order of the channel. In the figure (1) 'NL' represents nonlinearity introduced in the linear dispersive channel. The nonlinear channel equation used in this paper is a general form of difference equation. The output of the nonlinear channel  $b(n)$  is represented as

$$b(n) = k_0 s(n) + k_1 \tanh^2(s(n-1)) \quad (2)$$

where the nonlinearity coefficients are  $k_0=1$  and  $k_1=0.8$ .

The channel output  $b(n)$  is added with Additive White Gaussian Noise  $g(n)$ . The transmitted signal  $s(n)$  is received as  $r(n)$  at the receiver end.

At the receiver section, the work of equalizer is to recover the transmitted signal  $s(n)$  from the delayed desired signal  $d(n)$ . The error between the estimated output and desired output signal is defined as

$$e(n) = d(n) - y(n) \quad (3)$$

The adaptive equalization process reduces the error by updating the filter weights using adaptive algorithm. After training of equalizer the weights are fixed and used to obtain the original transmitted signal [6].

The implementation of QPSK is more useful than that of BPSK and also indicates the implementation of higher-order PSK. Usually the QPSK signals can be expressed as

$$\varphi_{QPSK}(t) = \sqrt{\frac{2E_b}{T_b}} \cos\left(2\pi f_c t + (2n-1)\frac{\pi}{4}\right) \quad (4)$$

where  $n=1, 2, 3, 4$

The term ' $E_b$ ' represents the energy of a symbol per bit. This yields the four phases  $\pi/4, 3\pi/4, 5\pi/4$  and  $7\pi/4$  as needed. This results in a two-dimensional signal space with unit basis functions

$$\psi_1(t) = \sqrt{\frac{2}{T_b}} \cos(2\pi f_c t) \quad (5)$$

$$\psi_2(t) = \sqrt{\frac{2}{T_b}} \sin(2\pi f_c t) \quad (6)$$

The first basis function is used as the in-phase component of the signal and the second as the quadrature component of the signal. Figure (2) represents the signal constellation consists of the signal-space 4 points  $\pm A$  and  $\pm A$  [1]. The value of  $A$  is expressed as

$$\pm A = \pm \sqrt{\frac{2E_b}{T_b}} \quad (7)$$

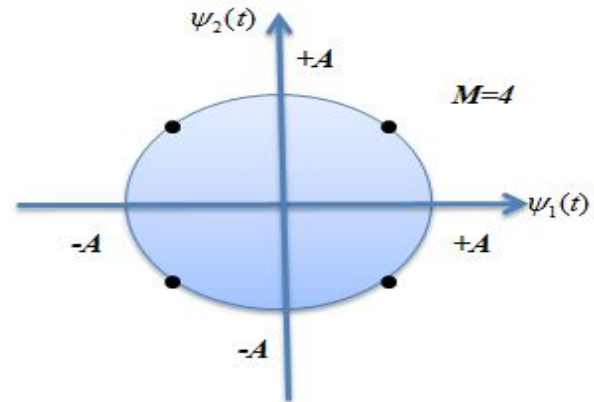


Fig.2. QPSK symbols in orthogonal signal space

### III. PROPOSED ALGORITHM

Adaptive filtering techniques are necessary consideration when a specific signal output is desired but the coefficients of filter cannot be determined at the outset. Sometimes this is because of changing line or transmission. The Least Mean Square (LMS) algorithm is generally used as an adaptive algorithm for optimization technique. The LMS model is to minimize the Euclidean norm by the help of a conventional least square fit analysis. LMS uses a gradient-based method of steepest decent and it uses the estimates of the gradient vector from the available data [10]. It incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error. In LMS Algorithm the simplified cost function,  $\xi_{LMS}(n)$  is given by

$$\xi_{LMS}(n) = 1/2 e^2(n) \quad (8)$$

where  $e(n)$  is defined as the error function which is the difference between the original output and estimated output of the adaptive filter. The cost function in (8) can be thought of as an instantaneous estimate of the MSE (mean square error) that is most useful in practical applications. The update LMS equation is given by

$$w(n+1) = w(n) + \mu e(n)x(n) \quad (9)$$

Equation (9) requires only multipliers and adders to implement. In fact, the number and type of operations needed for the LMS algorithm is nearly the same as that of the FIR filter structure with fixed coefficient values.

The convergence of the LMS algorithm is inversely proportional to the eigenvalue spread of the correlation matrix. When the eigenvalues are widespread, convergence may be very slow. The eigenvalue spread of the correlation matrix is estimated by computing the ratio of the largest eigenvalue to the smallest eigenvalue of the matrix. The step-size parameter or the convergence factor  $\mu$  is the basis for the convergence speed of the LMS algorithm. When  $\mu$  is small the convergence rate is slow, the error is still quite large. A moderately large value of  $\mu$  leads to faster convergence. However, when the value of  $\mu$  is too high it leads to the instability of the algorithm and leads to an erroneous result [10].

The performance of LMS algorithm is affected severely in presence of outliers. A simple and efficient normalized Sign Regressor LMS algorithm is suitable for applications requiring large signal to noise ratios with less computational complexity. The convergence speed of Sign LMS is faster

than the conventional LMS based realizations [11]. The weight update equation is given by

$$w(n+1) = w(n) + \mu e(n) \text{sign}(x(n)) \quad (10)$$

#### IV. FLANN AND SIGNED REGRESSOR FLANN

The basic principle of an FLANN is to expand the dimensionality of the input signal space by using a set of linearly independent functions. The expansion can produce complicated decision boundaries at the output space, so the FLANN is capable of dealing with linear inseparable problems [12]. The structure of FLANN used in channel equalization problem is shown in figure (3). It requires more no of sine and cosine functions that implies the computational complexity is more. The FLANN is a single layer network, where need of hidden layers is removed. In contrast to the linear weighting of the input pattern produced by the linear links of an MLP, the functional link acts on an element of a pattern or on the entire pattern itself by generating a set of linearly independent functions, and then evaluating these functions with the pattern as the argument. Thus, separability of input patterns is possible in the enhanced space [13].

However, the FLANN structure offers less computational complexity and higher convergence speed than MLP because of its single layer structure. The expanded function make use of a functional model comprising of a subset of orthogonal sine and cosine basis functions and the original pattern along with its outer products.

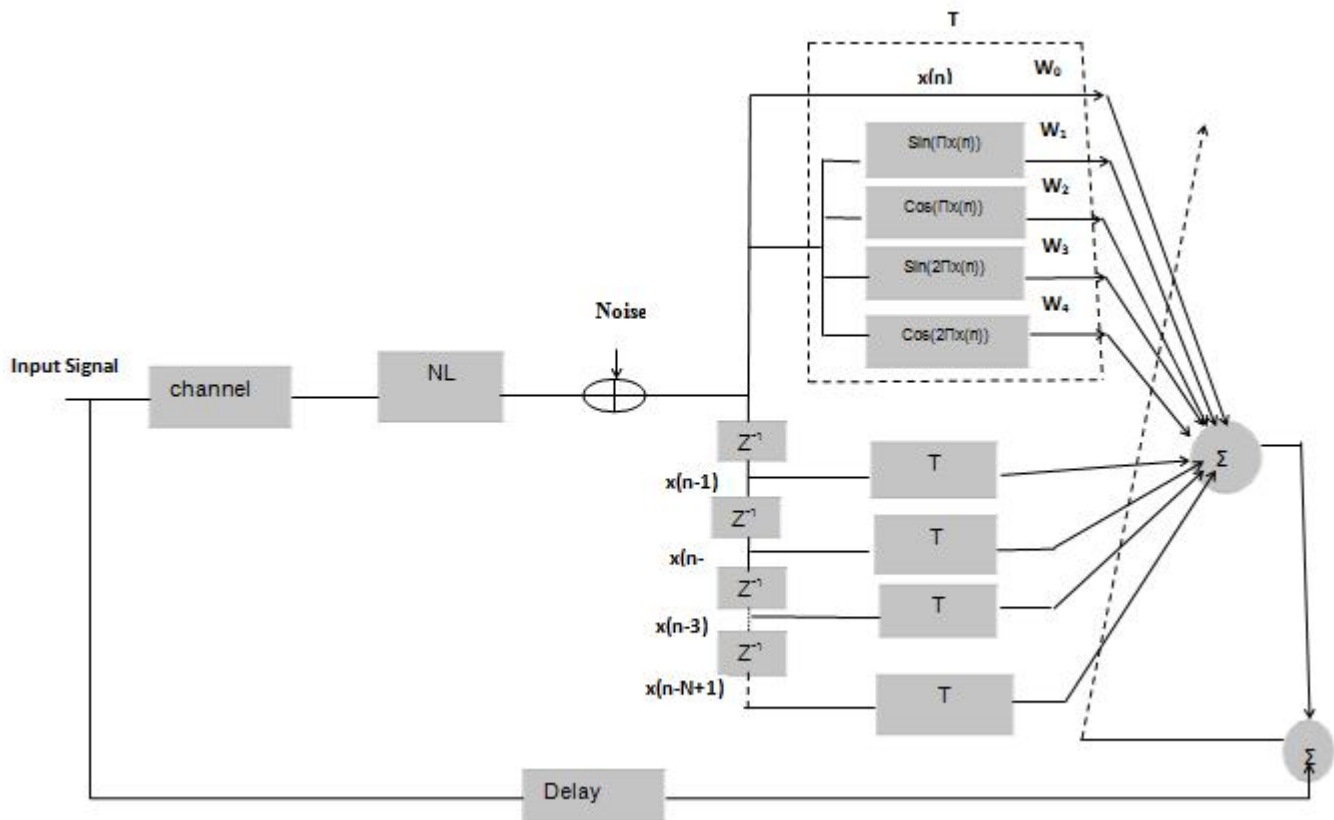


Fig. 3. Basic Structure of FLANN

Considering a two-dimensional input pattern  $u = [u_1 u_2]^T$ , the enhanced pattern is obtained as  $U^* = [u_1 \cos(\pi u_1) \sin(\pi u_1) \dots u_2 \cos(\pi u_2) \sin(\pi u_2) \dots U_1 U_2]^T$  and used by the network for the equalization purpose. The BP algorithm, is used to train the network, becomes very simple because of absence of any hidden layer. But the BP algorithm result converges very slowly for a predefined input samples. The learning ability and the justification for the use of trigonometric polynomial are described in [4]. Inspiring from the fact that Sign Regressor LMS performs faster convergence as compared to conventional LMS and is robust to the outliers and impulse noise present in the channel [11], the proposed Sign Regressor FLANN technique uses the signed inputs for the weight update equation for the channel equalization problem.

## V. RESULT & DISCUSSION

The performance of the proposed equalizer was validated using simulation studies. To study the effect of nonlinearity on the equalizer performance the channel in figure (1) has been introduced. Initially the equalizers were trained with 10,000 random samples between  $[-0.5 \ 0.5]$ . The simulations are conducted by taking learning rate parameter  $\mu$  as 0.01 and SNR as 15db. Here. The weight update equation is used for non-linear channel equalization. Here the performance of Signed Regressor FLANN is compared with the conventional FLANN. The convergence characteristics of the LMS, Signed Regressor LMS, FLANN and Signed Regressor FLANN have been depicted in figure (4-7).

### A. MSE Analysis for Nonlinear Channel

The non-linear channel used in this proposed model is taken from equation (2). The training performances of equalizers were demonstrated. The MSE was plotted at each iteration and the convergence of the adaptive algorithm is evaluated from the MSE plot.

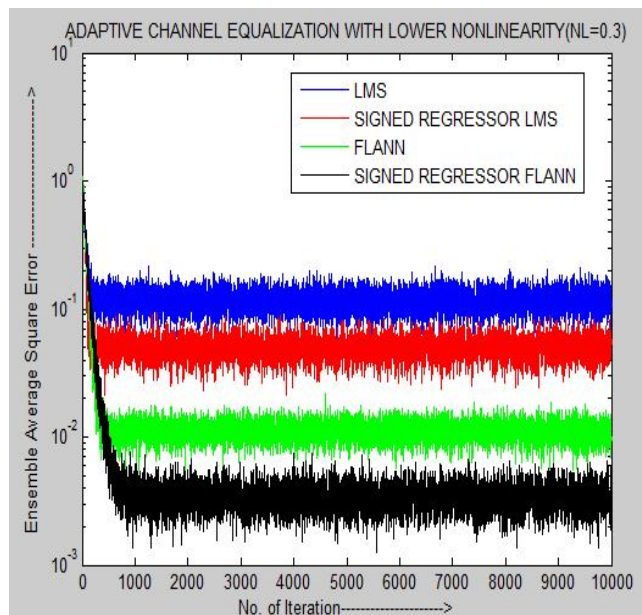


Fig. 4. MSE using LMS and FLANN with lower nonlinearity (NL=0.3)

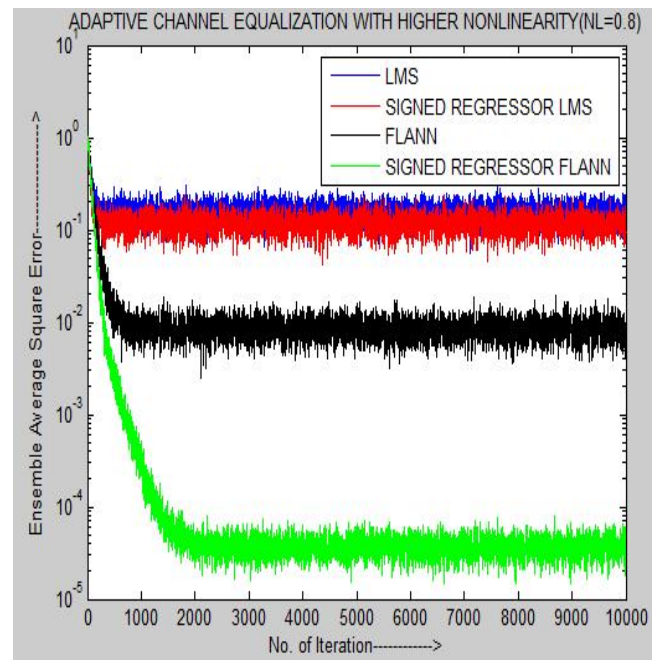


Fig. 5. MSE using LMS and FLANN with higher nonlinearity (NL=0.8)

From figure (4-5), it is concluded that the proposed Signed Regressor FLANN algorithm shows better MSE performance compared to conventional LMS and FLANN for different nonlinearity factor. However the MSE converges quickly in the proposed model.

### B. MSE vs SNR

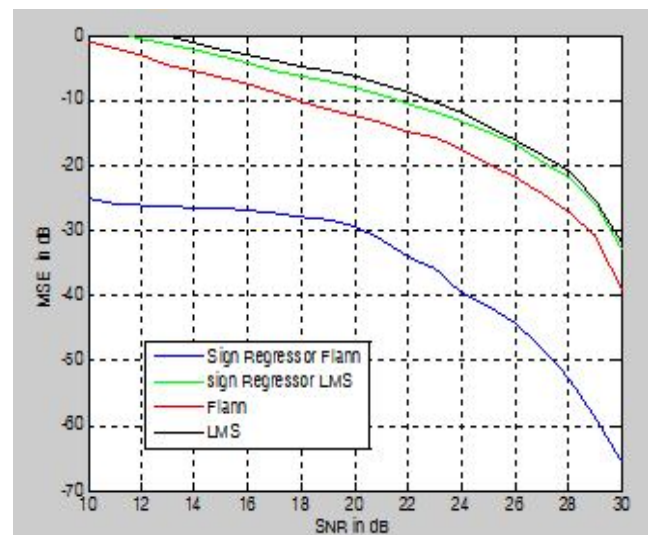


Fig. 6. Steady state MSE performance with variation of SNR

Figure (6) shows the MSE performance of the different equalizers with the variation of SNR values for the channel model. As SNR increase the MSE decreases for all the equalizers. The Sign Regressor FLANN equalizers maintain the least MSE i.e. -65.88 dB for variation of SNR values from 10dB to 30dB.

### C. BER Analysis

The bit error rate (BER) performance provides the actual

performance of the equalizers. The performance of the Signed Regressor FLANN is analyzed using BER as performance index.

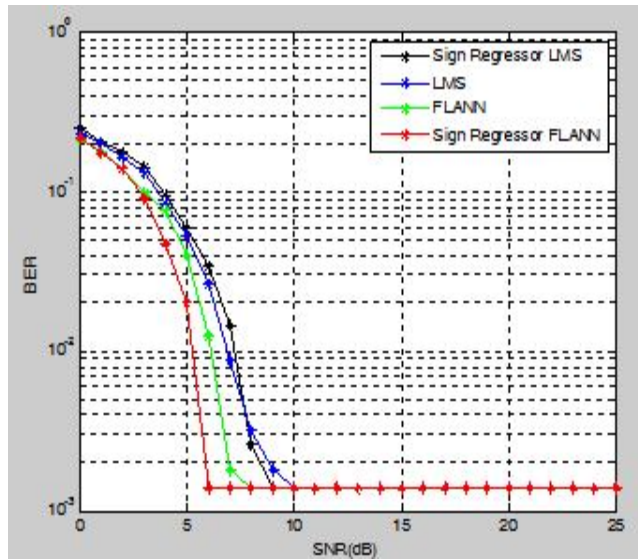


Fig. 7. Effect of variation of SNR on the BER performance

Figure (7) shows the BER performance of different equalizers using variable SNR. Here it has been observed that the BER remains constant after some SNR values. This constant value comes from the fact that there are a constant number of error bits which is introduced. These error bits are initial bits till the delay is matched.

## VI. CONCLUSION

Here a Signed Regressor FLANN based nonlinear channel equalizer has been presented to combat the inter-symbol interference (ISI) in wireless communication system. The simulation results show that the proposed algorithm performs superior to LMS, RLS in noisy environment and also capable of constructing a simple network whose performance is close to the optimal solution. The proposed FLANN model can also be the solution for the complex hybrid systems because of the simple architecture.

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